J Arid Land (2024) 16(3): 396–414
https://doi.org/10.1007/s40333-024-0094-z

Science Press Springer-Verlag

Spatiotemporal characteristics of cultivated land use eco-efficiency and its influencing factors in China from 2000 to 2020

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Abstract: Improving cultivated land use eco-efficiency (CLUE) can effectively promote agricultural sustainability, particularly in developing countries where CLUE is generally low. This study used provincial-level data from China to evaluate the spatiotemporal evolution of CLUE from 2000 to 2020 and identified the influencing factors of CLUE by using a panel Tobit model. In addition, given the undesirable outputs of agricultural production, we incorporated carbon emissions and nonpoint source pollution into the global benchmark-undesirable output-super efficiency-slacks-based measure (GB-US-SBM) model, which combines global benchmark technology, undesirable output, super efficiency, and slacks-based measure. The results indicated that there was an upward trend in CLUE in China from 2000 to 2020, with an increase rate of 2.62%. The temporal evolution of CLUE in China could be classified into three distinct stages: a period of fluctuating decrease (2000–2007), a phase of gradual increase (2008–2014), and a period of rapid growth (2015–2020). The major grain-producing areas (MPAs) had a lower CLUE than their counterparts, namely, non-major grain-production areas (non-MPAs). The spatial agglomeration effect followed a northeast-southwest strip distribution; and the movement path of barycentre revealed a "P" shape, with Luoyang City, Henan Province, as the centre. In terms of influencing factors of CLUE, investment in science and technology played the most vital role in improving CLUE, while irrigation index had the most negative effect. It should be noted that these two influencing factors had different impacts on MPAs and non-MPAs. Therefore, relevant departments should formulate policies to enhance the level of science and technology, improve irrigation condition, and promote sustainable utilization of cultivated land.

Keywords: cultivated land use eco-efficiency (CLUE); slacks-based measure (SBM) model; barycentre model; standard deviation ellipse (SDE); panel Tobit model; carbon emissions; nonpoint source pollution

Citation: LI Shaoting, MU Na, REN Yanjun, Thomas GLAUBEN. 2024. Spatiotemporal characteristics of cultivated land use eco-efficiency and its influencing factors in China from 2000 to 2020. Journal of Arid Land, 16(3): 396–414. https://doi.org/10.1007/s40333-024-0094-z

1 Introduction

Cultivated land, a fundamental resource for agricultural production and the cornerstone of human survival (Lambin et al., 2013), plays a critical role in guaranteeing national food security (Quaye et al., 2010). To improve the quality of cultivated land, many countries have given great consideration to the conservation of cultivated land ecosystems (van Uytvanck et al., 2010; Nitsch et al., 2012; Glackin et al., 2016). Although cultivated land is better used than before, there are still

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Received 2023-09-22; revised 2024-01-08; accepted 2024-01-19

major challenges to its sustainability. It has been reported that by 2050, the world population is expected to exceed 9.80×10^{10}, and the demand for food will increase by more than 50.00% (FAO et al., 2021), which puts forward higher requirements for the production capacity of cultivated land. Moreover, the advancement of urbanization has generated more land demand (Song and Pijanowski, 2014), resulting in a sharp reduction in the amount of arable land (van Vliet et al., 2015). Moreover, the excessive use of agricultural production inputs (e.g., chemical fertilizer, pesticide, agricultural film, etc.) has seriously endangered the local ecological environment and biodiversity (Potts et al., 2010; Bommarco et al., 2013; Newbold et al., 2015; Huang et al., 2022), which in turn reduces the productivity of cultivated land (Ray et al., 2012). Improving cultivated land use eco-efficiency (CLUE) has therefore become an essential means of sustaining cultivated land productivity (Garnett et al., 2013; Weltin et al., 2018).

In particular, China, as a developing economy, is facing major challenges in improving its CLUE. With only 7.00% of the world's total cultivated land, China feeds 22.00% of the world's population (Huang et al., 2019). Moreover, the continuous population increase and marked changes in residents' dietary structure put forward higher requirements for the quality and quantity of food in the future, which means that the comprehensive production capacity of cultivated land needs to be further improved (Qi et al., 2015). Unfortunately, the conflicts between cultivated land use and environmental protection are becoming increasing prominent (Chen, 2007; Liu et al., 2020). For instance, the excessive use of pesticides and fertilizers has caused serious damage to the ecological environment, leading to increased carbon emissions, nonpoint source pollution, and cultivated land degradation (Sun et al., 2018; Jawaduddin et al., 2019; Nkansah et al., 2019; Heidenreich et al., 2022). If the above problems are not resolved, the sustainable utilization of limited cultivated land will not be achieved, let alone national food security.

The CLUE has been evaluated by numerous scholars, but the methods of estimation and relevant indicators need to be further improved. Most studies used slacks-based measure (SBM)-undesirable cross-sectional model to measure CLUE. For instance, Zhang et al. (2020) used this model to evaluate the CLUE in Zhejiang Province, China and explored its spatial-temporal evolution. As introduced by Schaltegger and Sturm (1990) and Bonfiglio et al. (2017), eco-efficiency is vital for evaluating the relationship between economic activities and environmental impacts. The goal of CLUE calculation is to achieve coordinated and efficient development of "resource-economy-environment" in cultivated land use (Coluccia et al., 2020), that is, to maximize the expected output while minimizing both resource consumption and environmental pollution (Todorovic et al., 2016). Therefore, evaluating the ecological efficiency of agricultural production should also consider environmental damage (Sabiha et al., 2017). Given that most aspects of agricultural production emit greenhouse gases (GHGs), agriculture has always been considered a significant source of GHG emissions (Luo et al., 2020). An increase in GHG emissions can lead to climate problems, including global warming, extreme drought, and glacial melting (Xiao et al., 2023). Correspondingly, carbon emissions from agricultural production should also be considered as an undesired output when using SBM model to measure CLUE (Han and Zhang, 2020; Kuang et al., 2020). However, most studies only considered carbon emissions while ignoring the nonpoint source pollution caused by nitrogen and phosphorus losses from chemical fertilizers, which increases the bias in measuring CLUE. Although a few existing studies considered both, the study area has focused on regions rather than the whole of China (Yang et al., 2022; Wang et al., 2023). In addition, the SBM-undesirable cross-sectional model assumes that the production technology is constant throughout the study period, which does not correspond to reality. More specifically, it can be used only to evaluate each decision-making unit in the same year and cannot accurately reflect the interannual changes in CLUE.

The influencing factors of CLUE are hot spots in land use research field. For instance, Zhang et al. (2021) analyzed the impact of agricultural subsidies on CLUE, and the results demonstrated that subsidies are not helpful in maintaining a balance between crop cultivation and ecological governance. Yang et al. (2013, 2016) found that off-farm employment does not harm CLUE among

more than 2000 households in 5 provinces of China. The reason is that agricultural mechanization can offset the loss of labour transfer. In contrast to the above view, Zhao et al. (2021) revealed a robust U-shaped relationship between off-farm employment and CLUE after exploring data from 1961 counties in China. In addition, other factors, including but not limited to natural disasters, planting structure, multiple crop indices, industrialization level, and land fragmentation, also have different effects on CLUE (Hou et al., 2021; Yang et al., 2021). Notably, CLUE is the result of interactions among several essential factors, including natural, social, and economic aspects (Toma et al., 2017; Li et al., 2019). Most studies used multiple linear regression and index decomposition methods to analyze the factors that affect CLUE (Wang and Li, 2014; Han and Zhang, 2020). The CLUE is a truncated variable and requires a more plausible econometric method, such as the panel Tobit model, to obtain unbiased estimates.

In summary, the key questions to be addressed in this study are as follows: (1) how can China's CLUE be measured more accurately? (2) what are the temporal and spatial evolution characteristics of CLUE in China? (3) what factors influence CLUE? and (4) what types of policies should be formulated to enhance CLUE and achieve the sustainable use of cultivated land resources? To resolve these questions, firstly, we incorporated carbon emissions and nonpoint source pollution into the global benchmark-undesirable output-super efficiency-slacks-based measure (GB-US-SBM) model, i.e., a model combines global benchmark technology, undesirable output, super efficiency, and slacks-based measure method, as undesired outputs to measure the CLUE in 31 provinces, autonomous regions, and municipalities of China (excluding Hong Kong Special Administrative Region, Macao Special Administrative Region, and Taiwan Province due to no data available); secondly, we adopted barycentre model and standard deviation ellipse (SDE) to investigate the spatial-temporal evolution of CLUE in China from 2000 to 2020; and thirdly, we used panel Tobit model to analyze the influencing factors of CLUE and explain the underlying reasons.

Compared with previous research, this study made several contributions. First, using GB-US-SBM model can obtain more comprehensive and accurate CLUE measurement results. More specifically, the results displayed the same production frontier and were thus intertemporally comparable, revealing how the CLUE in China changes with time and space at the macro level. Second, based on national-level analysis, this paper explained the differences in CLUE and its influencing factors between major grain-producing areas (MPAs) and non-major grain-producing areas (non-MPAs), which is innovative from a research perspective. The MPAs of China include 12 provinces and 1 autonomous region, namely Hebei, Liaoning, Jilin, Heilongjiang, Jiangsu, Anhui, Jiangxi, Shandong, Henan, Hubei, Hunan, and Sichuan provinces and Inner Mongolia Autonomous Region; while the remaining provinces, autonomous regions, and municipalities are non-MPAs, including Zhejiang, Fujian, Guangdong, Hainan, Shanxi, Guizhou, Yunnan, Shaanxi, Gansu, and Qinghai provinces, Guangxi Zhuang Autonomous Region, Ningxia Hui Autonomous Region, Xizang Autonomous Region, Xinjiang Uygur Autonomous Region, Beijing, Tianjin, Shanghai, and Chongqing. Third, in terms of the research context, this study focused on China where there is a serious conflict between land use and economic development. In this way, we can not only provide valuable targeted policy suggestions for China to improve its CLUE, but also establish an example for other developing countries to achieve sustainable utilization of cultivated land.

2 Materials and methods

2.1 Data and variables

2.1.1 Data sources

The research sample comprised environmental and socio-economic data obtained from 31 provinces, autonomous regions, and municipalities in China from 2000 to 2020 (excluding Hong Kong Special Administrative Region, Macao Special Administrative Region, and Taiwan Province

due to no data available). The input-output indicators of CLUE and its influencing factors were primarily sourced from the China Statistical Yearbook (National Bureau of Statistics of China, 2001–2021a), the China Rural Statistical Yearbook (National Bureau of Statistics of China, 2001–2021b), and the National Bureau of Statistics (https://data.stats.gov.cn/easyquery.htm) and the Express Professional Superior (EPS) data platform (http://olap.epsnet.com.cn/) at the provincial level. In the case of missing data, interpolation method was employed for supplementation. Furthermore, to mitigate the influence of price fluctuations, the indicators of GDP per capita and total agricultural output value were adjusted for inflation using the year 2000 as the base period, which ensures comparability across different time points.

2.1.2 Connotation of CLUE

According to WBCSD (1996), eco-efficiency refers to the use of resources to meet human needs while minimizing environmental outcomes. In other words, human welfare should be maximized with minimum resource consumption and environmental pollution. Thus, eco-efficiency covers three aspects: natural resource, socioeconomic situation, and environment, and is a compound concept related to the coordinated development of the three aspects (Deng and Gibson, 2019).

Cultivated land is one of the most important factors for agricultural production and human survival. The optimal state of cultivated land use should achieve the highest economic and social output with the least input of production elements while minimizing the negative impact on environment (Yang et al., 2021). Specifically, the agricultural output value reflects the economic value of cultivated land utilization, while grain output represents the ability of cultivated land to guarantee food security. Therefore, these two indicators can characterize the desirable output of cultivated land utilization, that is, the socioeconomic output. In addition, GHG emissions and nonpoint source pollution caused by inputs of production elements such as pesticides and fertilizers should be regarded as undesirable outputs (i.e., environmental pollution). Based on this, we defined CLUE as the degree to which socioeconomic output can be maximized and environmental pollution can be minimized given specific inputs of production elements in the process of cultivated land use (Fig. 1).

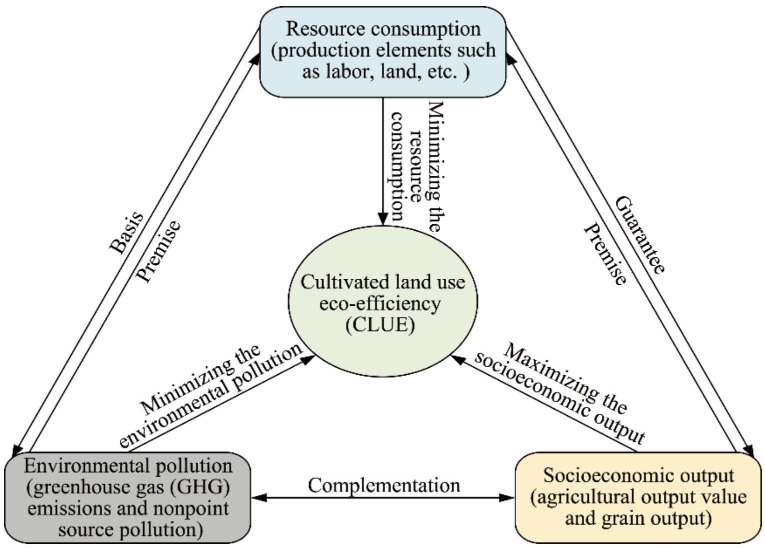

Fig. 1 Connotation of cultivated land use eco-efficiency (CLUE) in this study

2.1.3 Indicators used to measure CLUE

Referring to Luo et al. (2020) and Yin et al. (2022), we selected ten indicators to construct the CLUE measurement system. The input indicators encompass various factors, such as land, labor, agricultural machinery, pesticide, chemical fertilizer, and agricultural film. The desirable output

indicators include the total agricultural output value and the total grain output, which represent the socioeconomic aspect. The undesirable output indicators encompass carbon emissions and nonpoint source pollution, which represent the environmental aspect. Table 1 presents the definitions and descriptive statistics of these ten indicators, offering a comprehensive overview.

Table 1 Evaluation indicator system of cultivated land use eco-efficiency (CLUE) in this study

Indicator		Definition	Mean	SD
Input	Land	Total sown area of crops ($\times 10^3$ hm^2)	5154.20	3733.38
	Labor	Labor was calculated as the employee numbers in the primary industry multiplied by the proportion of total agricultural output value to the gross output value of primary industry ($\times 10^4$ persons).	496.30	389.30
	Agricultural machinery	Total power of agricultural machinery ($\times 10^4$ kW)	2763.18	2687.36
	Pesticide	Usage of pesticide ($\times 10^4$ t)	5.06	4.22
	Chemical fertilizer	Net amount of chemical fertilizer usage ($\times 10^4$ t)	169.62	138.49
	Agricultural Film	Usage of agricultural film ($\times 10^4$ t)	6.78	6.35
Desirable output	Total agricultural output value	Total agricultural output value ($\times 10^8$ CNY)	769.98	630.59
	Total grain output	Total grain output ($\times 10^4$ t)	1818.10	1587.47
Undesirable output	Carbon emissions	Total carbon emissions ($\times 10^4$ t)	255.10	194.22
	Nonpoint source pollution	Total loss of fertilizer nitrogen and phosphorus, pesticide, and agricultural film ($\times 10^4$ t)	20.84	16.27

Note: SD, standard deviation. Mean is the average value of indicator of all the 31 provinces, autonomous regions, and municipalities during the study period.

Carbon emissions predominantly originate from four sources. The first source comprises pesticides, chemical fertilizers, and agricultural films used on cultivated land. The second source is diesel fuel consumed by agricultural machinery. The third source is the consumption of electrical energy provided by thermal power generation (i.e., irrigation). The fourth source is plowing. The formula for determining carbon emissions is as follows:

$$U_1 = \sum E_i = \sum \left(T_i \times \delta_i\right), \tag{1}$$

where U_1 is the total carbon emissions ($\times 10^4$ t); E_i is the carbon emissions originating from all sources ($\times 10^4$ t); T_i is the original amount of all the carbon sources; and δ_i is the carbon emission coefficient (Table 2).

Table 2 Carbon emission coefficient of each kind of carbon source evaluated by this study

Classification	Carbon source	Coefficient	Reference
The first source	Pesticide (kg)	4.9341 kg/kg	Post and Kwon (2000)
	Chemical fertilizer (kg)	0.8956 kg/kg	West and Marland (2002)
	Agricultural film (kg)	5.1800 kg/kg	Li et al. (2011)
The second source	Diesel fuel (kg)	0.5927 kg/kg	Li et al. (2011)
The third source	Irrigation (hm^2)	25.0000 kg/hm^2	Dubey and Lal (2009)
The fourth source	Plowing (hm^2)	3.1260 kg/hm^2	Wu et al. (2007)

Nonpoint source pollution mainly stems from the inappropriate use of chemical fertilizers, pesticides, and agricultural films, and its calculation can be performed using Equation 2.

$$U_2 = TN \times \rho_i + TP \times \eta_i + TC \times \mu_i + TF \times \varepsilon_i, \tag{2}$$

where U_2 is the total amount of nonpoint source pollution ($\times 10^4$ t); TN is the total amount of nitrogen ($\times 10^4$ t); TP is the total amount of phosphorus (P_2O_5) ($\times 10^4$ t); ρ_i and η_i are the loss coefficients of nitrogen and phosphorus, respectively; TC is the usage of pesticide (10^4 t); TF is the usage of agricultural film ($\times 10^4$ t); and ε_i and μ_i are the residual coefficients of pesticide and

agricultural film, respectively. All coefficients were determined from the China Pollution Source Census (State Council of China, 2009).

2.1.4 Variables measuring the influencing factors of CLUE

The spatial-temporal evolution of CLUE results from the interaction of many factors. Drawing upon the literature, we selected influencing factors from five dimensions, namely, natural condition, regional economic development level, agricultural production condition, science and technology level, and agricultural business scale. Considering the availability of data, we selected five variables, namely, the multiple cropping index (MCI), GDP per capita (GPC), irrigation index (II), investment in science and technology (STI), and sown area per labourer (SAL), to quantitatively analyze their effects on CLUE (Table 3).

Table 3 Selected influencing factors of cultivated land use eco-efficiency (CLUE) by this study

Dimension	Variable	Description	Mean	SD	Minimum	Maximum
Natural condition	MCI	Proportion of total sown area of crops to total cultivated area (%)	1.25	0.39	0.48	2.29
Regional economic development level	GPC	Gross domestic product (GDP) per capita ($\times10^4$ CNY/person)	2.13	1.44	0.27	8.57
Agricultural production condition	II	Proportion of effective irrigated area to total cultivated area (%)	0.52	0.23	0.14	1.18
Science and technology level	STI	Proportion of local expenditures on science and technology to general budgetary expenditures of local governments (%)	1.83	0.01	0.30	7.20
Agricultural business scale	SAL	Total sown area of crops divided by agricultural labour (hm^2/person)	1.17	0.59	0.47	4.41

Note: MCI, multiple cropping index; GPC, GDP per capita; II, irrigation index; STI, investment in science and technology; SAL, sown area per labourer; SD, standard deviation. Mean is the average value of indicator of all 31 provinces, autonomous regions, and municipalities during the study period, while minimum and maximum are the minimum value and maximum value of indicator of all 31 provinces, autonomous regions, and municipalities during the study period, respectively.

2.2 Methodology

2.2.1 GB-US-SBM model

Unlike the traditional data envelopment analysis (DEA) model (Charnes et al., 1978), the SBM model first proposed by Tone (2001) is non-radial and non-oriented, and can return an efficiency value between 0 and 1, of which 1 means that the decision-making units (DMUs) are SBM efficient, while 0 means inefficient. Based on this, Tone (2002) modified the former model and proposed the super-efficiency SBM to rank these efficient DMUs. We all know that undesirable output is an important part of evaluating efficiency. Tone (2004) incorporated undesirable outputs into an evaluation model and proposed a new SBM model with undesirable outputs. However, these models construct the production frontier based on cross-sectional data, and the measurement results are thus not intertemporally comparable. Referring to the relevant literature (Pastor and Lovell, 2005; Huang et al., 2014), this study constructed the GB-US-SBM model, which combines global benchmarks, undesirable outputs, super-efficiency aspects into a SBM model to measure CLUE.

Assuming that there are N DMUs and a period of T (t=1, 2, ..., T), and according to the constant return to scale, we defined the set of production possibilities as follows:

$$P=\left\{\left(x,y^{g},y^{b}\right)\middle|x_T\geq\sum_{j=1}^{N}\sum_{\tau=1}^{T}\lambda_{j\tau}x_{j\tau},\ y_T^{g}\leq\sum_{j=1}^{N}\sum_{\tau=1}^{T}\lambda_{j\tau}y_{j\tau}^{g},y_T^{b}\geq\sum_{j=1}^{N}\sum_{\tau=1}^{T}\lambda_{j\tau}y_{j\tau}^{b}\right\}\left(\lambda\geq0;j\neq0,\text{if }\tau=t\right), \quad (3)$$

where P is the set of production possibilities; $x_{j\tau}$, $y_{j\tau}^{g}$, $y_{j\tau}^{b}$, and $\lambda_{j\tau}$ are the four vectors that can express the inputs, desirable outputs, undesirable outputs, and weight of DMU$_j$ (i.e., the j^{th} DMU) at time t, respectively; g and b are the good and bad outputs, respectively; N is the number of DMUs; x_T, y_T^{g}, and y_T^{b} are the total inputs, total desirable outputs, and total undesirable outputs,

respectively; T is the time span; and λ is the nonnegative weight vector.

The GB-US-SBM model can be described by Equation 4.

$$\rho_{0t}^{G*}=\min\frac{1+\frac{1}{m}\sum_{i=1}^{m}\frac{s_{i0t}^{-}}{x_{i0t}}}{1-\frac{1}{s_1+s_2}\left(\sum_{r=1}^{s_1}\frac{s_{r0t}^{g}}{y_{r0t}^{g}}+\sum_{q=1}^{s_2}\frac{s_{q0t}^{b}}{y_{q0t}^{b}}\right)}\text{subject to}\begin{cases}x_{0t}-\sum_{j=1}^{N}\sum_{\tau=1}^{T}\lambda_{j\tau}x_{j\tau}+s_{0t}^{-}\geq 0\\ \sum_{j=1}^{N}\sum_{\tau=1}^{T}\lambda_{j\tau}y_{j\tau}^{g}-y_{0t}^{g}+s_{0t}^{g}\geq 0\\ y_{0t}^{b}-\sum_{j=1}^{N}\sum_{\tau=1}^{T}\lambda_{j\tau}y_{j\tau}^{g}+s_{0t}^{b}\geq 0\\ 1-\frac{1}{s_1+s_2}\left(\sum_{r=1}^{s_1}\frac{s_{r0t}^{g}}{y_{r0t}^{g}}+\sum_{q=1}^{s_2}\frac{s_{q0t}^{b}}{y_{q0t}^{b}}\right)\geq\varepsilon\end{cases}\begin{pmatrix}s_{0t}^{-}\geq 0\\ s_{0t}^{g}\geq 0\\ s_{0t}^{b}\geq 0\\ \lambda_{0t}\geq 0\\ j\neq 0,\text{if }\tau=t\end{pmatrix},\tag{4}$$

where ρ_{0t}^{G*} is the CLUE value of DMU_0; and s_{0t}^{-}, s_{0t}^{g}, and s_{0t}^{b} are the slack vectors of inputs, desirable outputs, and undesirable outputs of DMU_0 at time t, respectively; s_{i0t}^{-}, s_{r0t}^{g}, and s_{q0t}^{b} are the slack vectors of the i^{th} input, r^{th} desirable output, and q^{th} undesirable output of DMU_0 at time t, respectively; x_{0t} is the inputs of DMU_0 at time t; y_{0t}^{g} is the desirable outputs of DMU_0 at time t; y_{0t}^{b} is the undesirable outputs of DMU_0 at time t; y_{r0t}^{g} is the r^{th} desirable output of DMU_0 at time t; y_{q0t}^{b} is the q^{th} undesirable output of DMU_0 at time t; λ_{0t} is the weight of DMU_0 at time t; m, s_1, and s_2 are the number of inputs, desirable outputs, and undesirable outputs, respectively; and ε is the non-Archimedean infinitesimal. If $\rho_{0t}^{G*}\geq 1$, all the values of slack variables are zero, then DMU_0 is efficient; while if $\rho_{0t}^{G*}<1$, DMU_0 is inefficient, that is, the values of slack variables of inputs and outputs should be further improved.

2.2.2 Barycentre model

As a useful analytical tool for revealing changes in spatial patterns, the barycentre model can concisely and intuitively describe the spatial distribution of research objects (Griffith, 1984; Wang et al., 2018). In this study, we used the barycentre model to analyze the spatial evolution of CLUE in China. The calculation formulas for barycentric coordinates are as follows:

$$x_b=\frac{\sum_{a=1}^{n}T_{ab}x_a}{\sum_{a=1}^{n}T_{ab}};y_b=\frac{\sum_{a=1}^{n}T_{ab}y_a}{\sum_{a=1}^{n}T_{ab}},\tag{5}$$

where T_{ab} is the value of the a^{th} province, autonomous region, and municipality in the b^{th} year; (x_a, y_a) is the spatial coordinate of the a^{th} province; (x_b, y_b) is the barycentre coordinate of CLUE in the b^{th} year; and n is the number of province, autonomous region, and municipality.

Assuming that the barycentric coordinates at k and $k+z$ year are (x_k, y_k) and (x_{k+z}, y_{k+z}), respectively, we calculated the moving direction from (x_k, y_k) to (x_{k+z}, y_{k+z}) by Equation 6.

$$\theta_z=\arctan\left(\frac{y_{k+z}-y_k}{x_{k+z}-x_k}\right),\tag{6}$$

where θ_z is the moving direction.

The moving distance of barycentre is:

$$d_z=\sqrt{\left(y_{k+z}-y_k\right)^2+\left(x_{k+z}-x_k\right)^2},\tag{7}$$

where d_z is the moving distance.

2.2.3 SDE

The SDE has proven to be a reliable method for depicting the spatial distribution characteristics of

geographical elements (Lefever, 1926; Wong, 1999). Its utility extends across various disciplines, as evidenced by its widespread application in numerous fields (Yue et al., 2005; Mamuse et al., 2009; Vanhulsel et al., 2011). In this study, we used SDE to depict the spatial dynamic trend of China's CLUE. Four basic parameters, namely, the centre, primary axis, secondary axis, and azimuth, are contained in SDE (Zhang et al., 2022). The centre represents the relative position of geographic elements in a two-dimensional space; the azimuth denotes the main direction of distribution; and the primary axis and secondary axis indicate the extent of the main trend and sub-trend, respectively. The formulas are outlined below:

$$\overline{X}_w = \frac{\sum_{a=1}^{n} w_a x_a}{\sum_{a=1}^{n} w_a}; \overline{Y}_w = \frac{\sum_{a=1}^{n} w_a y_a}{\sum_{a=1}^{n} w_a}, \tag{8}$$

$$\tan\alpha = \frac{\sum_{a=1}^{n} w_a^2 \tilde{x}_a^2 - \sum_{a=1}^{n} w_a^2 \tilde{y}_a^2 + \sqrt{\left(\sum_{a=1}^{n} w_a^2 \tilde{x}_a^2 - \sum_{a=1}^{n} w_a^2 \tilde{y}_a^2\right)^2 + 4\sum_{a=1}^{n} w_a^2 \tilde{x}_a^2 \tilde{y}_a^2}}{2\sum_{a=1}^{n} w_a^2 \tilde{x}_a^2 \tilde{y}_a^2}, \tag{9}$$

$$\sigma_x = \sqrt{\frac{\sum_{a=1}^{n} \left(w_a \tilde{x}_a \cos\alpha - w_a \tilde{y}_a \sin\alpha\right)^2}{\sum_{a=1}^{n} w_a^2}}, \tag{10}$$

$$\sigma_y = \sqrt{\frac{\sum_{a=1}^{n} \left(w_a \tilde{x}_a \sin\alpha - w_a \tilde{y}_a \cos\alpha\right)^2}{\sum_{a=1}^{n} w_a^2}}, \tag{11}$$

where w_a is the weight of the a^{th} province, autonomous region, and municipality; ($\overline{X}_w$, $\overline{Y}_w$) is the weighted average centre coordinate; α is the azimuth; $\tilde{x}_a$ and $\tilde{y}_a$ are the deviation values of the x and y coordinates of the a^{th} province, autonomous region, and municipality from the centre of the ellipse, respectively; and σ_x and σ_y are the standard deviations along the x- and y-axes, respectively.

2.2.4 Panal Tobit model

We used panal Tobit regression model (Tobin, 1958; Simar and Wilson, 2007) to investigate the influencing factors of CLUE. Considering that the CLUE value calculated by the GB-US-SBM model is greater than 1.00, ordinary least squares (OLS) estimation is not suitable (Zhang et al., 2017b). The econometric model can be described as follows:

$$\text{CLUE}_{ab} = \beta_0 + \beta_1\text{MCI}_{ab} + \beta_2\text{GPC}_{ab} + \beta_3\text{II}_{ab} + \beta_4\text{STI}_{ab} + +\beta_5\text{SAL}_{ab} + \mu_{ab}, \tag{12}$$

where a and b are the a^{th} province, autonomous region, and municipality and b^{th} year, respectively; β_0, β_1, β_2, β_3, β_4, and β_5 are the coefficients of MCI, GPC, II, STI, and SAL, respectively; and μ is the stochastic error.

3 Results

3.1 Spatial-temporal evolution of CLUE

3.1.1 Interannual variation in CLUE

We inputted the input-output indicators into MaxDEA Ultra v.8.0 software (MaxDEA Software Ltd., Beijing, China) to measure the CLUE in China from 2000 to 2020. As depicted in Figure 2, both the mean and median exhibited similar trends, indicating an initial decrease followed by a

subsequent increase. The median was greater than the mean from 2018 to 2020, and the distribution pattern changed from right-skewed to left-skewed over time. After 2015, the interquartile range gradually increased, and the differences between provinces, autonomous regions, and municipalities became significant.

There was a noticeable upward trend in CLUE, with a growth rate of 2.62%. In detail, the temporal evolution of CLUE in China could be classified into three distinct stages: a period of fluctuating decrease (2000–2007), a phase of gradual increase (2008–2014), and a period of rapid growth (2015–2020). Specifically, the CLUE value experienced a decrease from 0.52 in 2000 to its lowest point of 0.41 in 2007, decreasing 0.11. From 2008 to 2014, there was a generally increasing trend in CLUE, except for that in 2009. The average annual growth rate during this period was 2.56%. After 2015, there was a remarkable and notable increase in CLUE, and it reached the peak value in 2020 (0.86), demonstrating a substantial increase of 0.33 and an average annual growth rate of 10.05%.

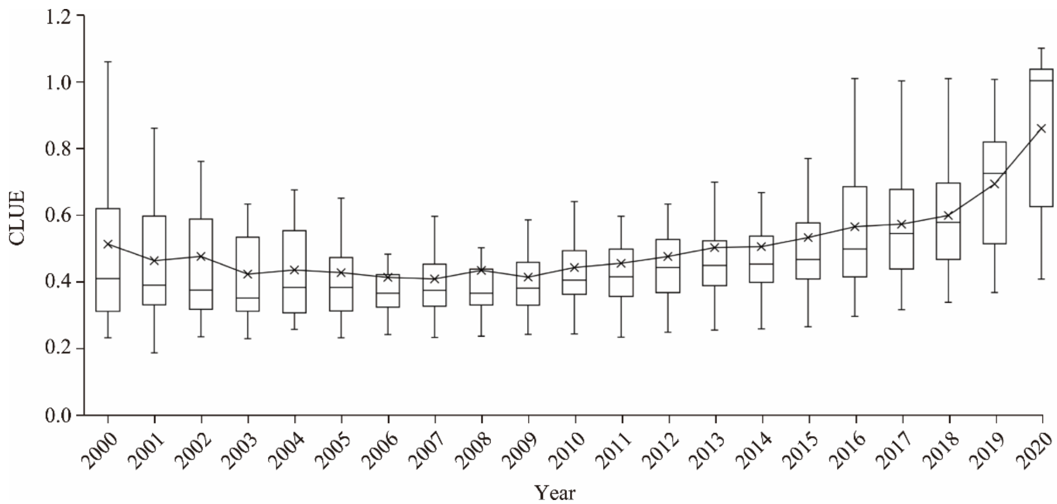

Fig. 2 Boxplot of CLUE in China from 2000 to 2020. The upper and lower boundaries of box indicate the 75% and 25% quantiles, respectively. The line within the box represents the median and the cross represents the average value. The upper boundary of error bar is equal to the 75th percentile plus 1.5 times interquartile range, while the lower boundary of error bar is equal to the 25th percentile minus 1.5 times interquartile range.

According to the results of temporal evolution of provincial CLUE (Fig. 3), CLUE increased in most provinces, autonomous regions, and municipalities. There were 16 provinces with a growth rate greater than 100.00%, of which Tianjin Municipality (269.70%) and Qinghai Province (254.79%) experienced the highest growth. It should be noted that among the 13 MPAs, only Liaoning (196.45%), Hebei (141.30%), Jiangsu (140.21%), Shandong (135.73%), and Henan (113.61%) provinces had a growth rate over 100.00% from 2000 to 2020, implying that the current situation of CLUE in MPAs is not good. Guizhou (7.92%) and Sichuan (0.23%) provinces had the lowest growth rate. The CLUE in Hainan, Sichuan, Guizhou, and Jiangxi provinces, Chongqing Municipality, and Xizang Autonomous Region showed a fluctuating downward trend. Among them, Jiangxi Province experienced the largest decrease, with an average annual decrease of 2.31%. Although MPAs constituted more than 75.00% of national grain production, the CLUE in MPAs still needs to be greatly improved.

3.1.2 Spatial evolution of CLUE

Four time points, 2000, 2007, 2014, and 2020, were selected to analyze the spatial distribution of CLUE in China at provincial-level (Fig. 4). In 2000, the CLUE was generally low, while Sichuan, Guizhou, Jiangxi, and Hainan provinces, as well as Chongqing Municipality and Xizang Autonomous Region performed relatively well than other provinces, autonomous regions, and municipalities. The CLUE in the southwestern regions surpassed that in the northeastern regions in

2000. In 2007, the CLUE of Hainan, Jilin, and Heilongjiang provinces and Xizang Autonomous Region decreased significantly, while the CLUE of Shandong, Hebei, and Qinghai provinces improved. Compared with the aforementioned provinces, autonomous regions, and municipalities, Guangxi Zhuang Autonomous Region and Gansu Province did not experience any significant changes. In 2014, the national CLUE level improved, of which Heilongjiang and Jilin provinces and Shanghai Municipality had the highest use efficiency, followed by Beijing Municipality and Jiangsu Province. By 2020, the CLUE of 18 provinces, autonomous regions, and municipalities, including Guizhou and Guangdong provinces and Tianjin Municipality, exceeded 1.00, indicating high efficiency. However, 7 provinces in MPA, namely Shandong, Hebei, Henan, Hubei, Hunan, Jilin, and Jiangxi provinces exhibited low efficiency. It can be observed that the CLUE in provincial-level changed significantly from 2000 to 2020 (Fig. 4).

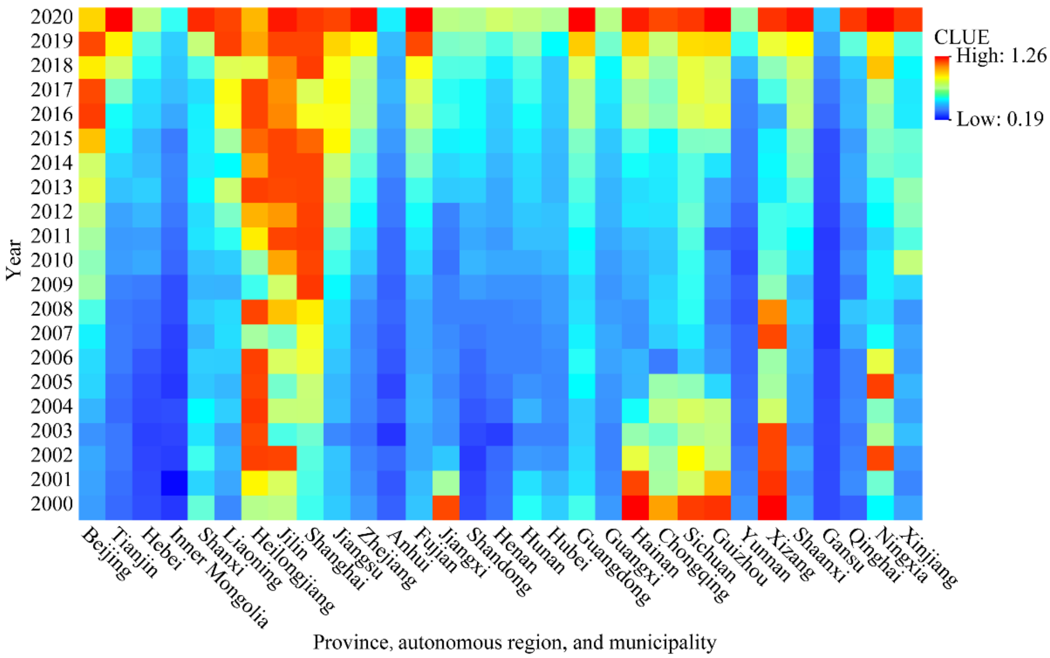

Fig. 3 Temporal change in CLUE of each province, autonomous region, and municipality in China from 2000 to 2020

We used ArcGIS v.10.5 software (Environment System Research Institute, California, USA) to determine the barycentre and movement paths of China's CLUE from 2000 to 2020 (Fig. 5). In most time, the barycentre was located in the central region of China (Henan Province). The barycentre moved in a "P" shape with the Luoyang City serving as the centre. The overall migration direction was "northeast–southwest". Specifically, the barycentre moved from southwest to northeast from 2000 to 2013; after 2013, it moved from northeast to southwest.

Table 4 displays the parameters of the CLUE barycentre in China spanning the period from 2000 to 2020. The barycentre underwent a displacement of 196.09 km by an average speed of 28.01 km/a toward the direction of 19°03′00″ east by north from 2000 to 2007. Subsequently, the moving speed decreased to 25.45 km/a during 2007–2014. From 2014 to 2020, the movement direction and distance changed. It moved 159.88 km with an average speed of 26.65 km/a toward 32°00′00″ west by south.

According to Table 5, we found three features of CLUE. In terms of distribution range, the area of SDE decreased from 47.45×10^5 in 2000 to 41.73×10^5 km^2 in 2016, and the spatial agglomeration effect of CLUE continued to increase. Since 2018, the ellipse area gradually increased and finally reached 45.31×10^5 km^2 in 2020, revealing an obvious spatial dispersion effect. The azimuth turned toward the southeast from 2000 to 2007, and it decreased after 2007, reaching a minimum of 38.24°

in 2016. After then the azimuth deflected toward the southeast again. For the distribution shape, the primary axis decreased from 1339.96 km in 2000 to 1017.41 km in 2016 and then gradually increased to 1278.14 km in 2020. The secondary axis, on the other hand, did not significantly change from 2000 to 2005. After that, the secondary axis increased sharply from 1077.54 km in 2006 to 1319.96 km in 2015, and then decreased continuously to 1128.47 km in 2020.

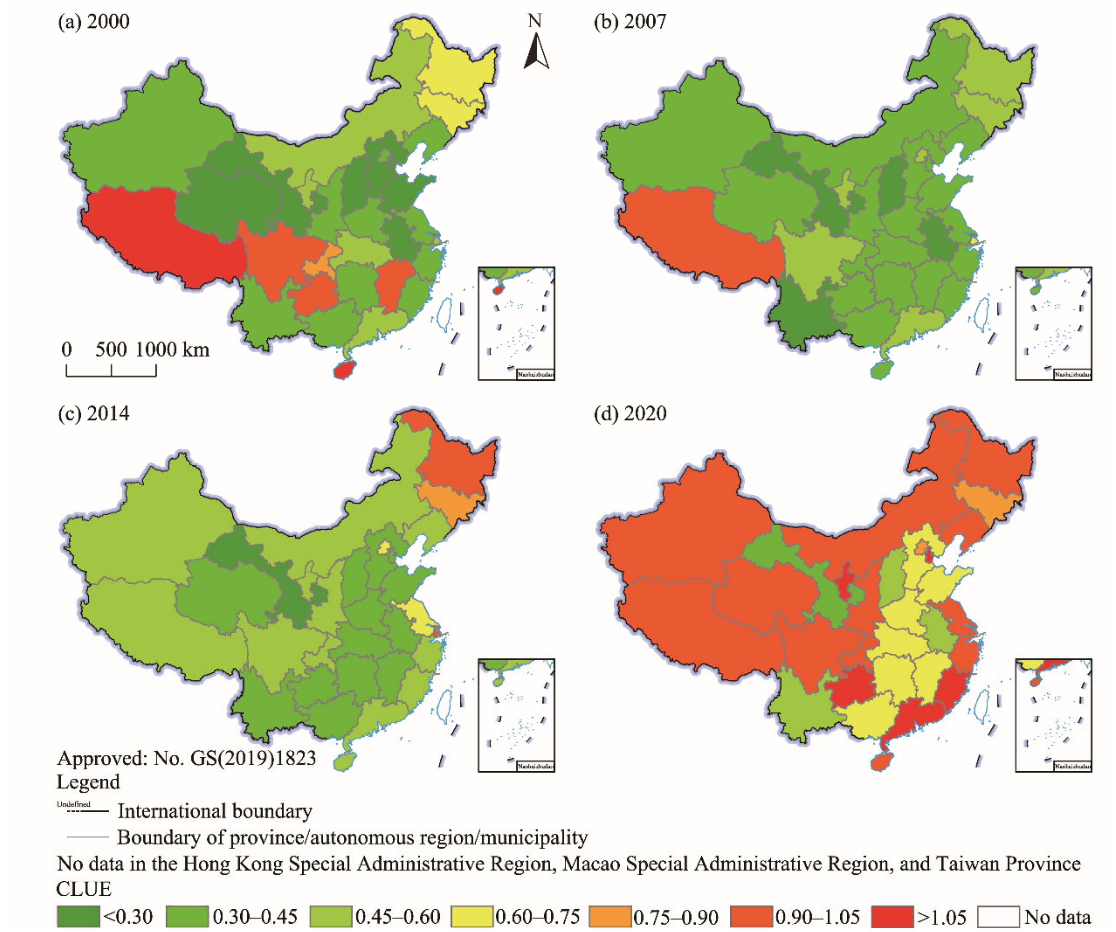

Fig. 4 Spatial distribution of CLUE in China in 2000 (a), 2007 (b), 2014 (c), and 2020 (d). Note that this map is based on the standard map (No. GS(2019)1823) of the Map Service System (http://bzdt.ch.mnr.gov.cn/) marked by the Ministry of Natural Resources of the People's Republic of China, and the base map has not been modified.

3.2 Factors influencing CLUE

Based on Equation 10, we utilized Stata v.17.0 software (StataCorp LLC, Texas, USA) to analyze the influencing factors of CLUE in China from 2000 to 2020. Table 6 displays the regression results. The results of Wald χ^2 test showed significance at 1% level, indicating a well-fitted model. The results of likelihood ratio test suggested the presence of individual effects in both MPAs and non-MPAs within China. Hence, it was suitable to use a panel Tobit model with random effects to analyze the data.

As reported in Table 6, all five variables (namely, MCI, GPC, II, STI, and SAL) were significant at 1% or 5% level, indicating that MCI, GPC, II, STI, and SAL are important factors that affect CLUE. For the natural condition dimension, the MCI had a significant positive effect on CLUE, with each unit increase in MCI resulting in 0.0980 units increase in CLUE. The MCI coefficient of MPAs was positive, but it did not pass the significance test. In contrast, MCI in non-MPAs could significantly improve CLUE level. For the regional economic development level dimension: the

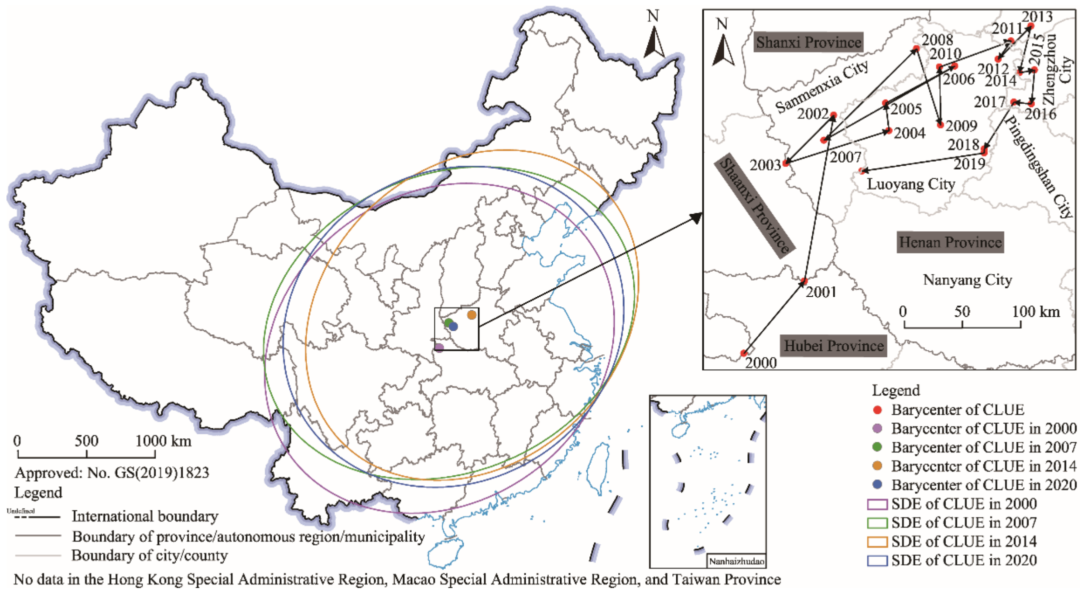

Fig. 5 Spatial evolution of CLUE in China from 2000 to 2020. Note that this map is based on the standard map (No. GS(2019)1823) of the Map Service System (http://bzdt.ch.mnr.gov.cn/) marked by the Ministry of Natural Resources of the People's Republic of China, and the base map has not been modified

Table 4 Barycentre parameters of CLUE in China from 2000 to 2020

Year	Latitude	Longitude	Location	Moving direction	Moving distance (km)	Moving speed (km/a)
2000	32°36′00″N	110°06′00″E	Shiyan City, Hubei Province	-	-	-
2007	34°11′24″N	110°58′12″E	Sanmenxia City, Henan Province	69°22′12″ east by north	196.09	28.01
2014	34°36′00″N	112°52′12″E	Zhengzhou City, Henan Province	19°03′00″ east by north	178.14	25.45
2020	33°56′24″N	111°18′36″E	Luoyang City, Henan Province	32°00′00″ west by south	159.88	26.65

Note: -, no data.

GPC positively influenced CLUE and had statistical significance at 1% level, aligning with the findings of McMillan et al. (1989). For the whole country, every unit increase in GPC increased the CLUE level by 0.0788 units. The GPC coefficient of non-MPAs was 0.0765, greater than that of MPAs (0.0671). Therefore, the regional economic development level had a more obvious effect on the improvement of CLUE in non-MPAs. For the agricultural production condition dimension, the II did not contribute positively to the improvement in CLUE, which is consistent with the findings of Kuang et al. (2020). Specifically, each unit increase in II reduced CLUE in the whole of China by 0.2240 units, and the negative impact of II on CLUE was more obvious in MPAs than in non-MPAs. For the science and technology level dimension: the STI had a significant positive influence on CLUE according to the calculation results of this study, providing support for the results of Luo et al. (2020). Nationwide, every unit increase in STI increased CLUE by 2.0760 units. In comparison to non-MPAs, MPAs exhibited a greater STI coefficient, suggesting that STI has a more pronounced promoting effect on CLUE in MPAs than in non-MPAs. For the agricultural business scale dimension: according to the results of this study, the SAL was beneficial for increasing CLUE, which is different from the findings of Yadav and Wang (2017). The reason might be that the per capita sown area in China is so small that it is far from reaching an appropriate scale. Thus, as the SAL increased, expanding the scale of operation in agriculture can significantly improve CLUE. One-unit increase in SAL led to 0.0931 units increase in CLUE. In addition, the influence of SAL on CLUE was greater in non-MPAs (0.1100) than in MPAs (0.0944).

Table 5 Standard deviation ellipse (SDE) parameters of CLUE in China from 2000 to 2020

Year	Area ($\times 10^5$ km^2)	XStdDist (km)	YStdDist (km)	Azimuth (°)	y/x-axis
2000	47.45	1339.96	1127.28	55.24	0.84
2001	49.38	1393.16	1128.21	48.43	0.81
2002	49.68	1451.66	1089.45	49.08	0.75
2003	49.72	1420.75	1114.04	58.76	0.78
2004	46.23	1381.06	1065.29	50.24	0.77
2005	44.79	1338.47	1064.88	54.06	0.80
2006	46.50	1373.37	1077.54	50.75	0.78
2007	47.55	1395.04	1084.99	67.01	0.78
2008	48.55	1439.49	1073.64	57.05	0.75
2009	44.91	1311.08	1090.46	58.88	0.83
2010	47.61	1342.38	1129.05	61.64	0.84
2011	46.47	1354.24	1092.38	49.93	0.81
2012	46.12	1339.03	1096.46	51.52	0.82
2013	45.67	1343.34	1082.25	48.35	0.81
2014	44.86	1325.58	1077.22	46.40	0.81
2015	43.99	1060.93	1319.96	44.42	1.24
2016	41.73	1017.41	1305.56	38.24	1.28
2017	42.14	1025.77	1307.82	41.30	1.27
2018	42.04	1050.66	1273.60	43.19	1.21
2019	42.86	1053.97	1294.60	42.60	1.23
2020	45.31	1278.14	1128.47	60.01	0.88

Note: XStdDist represents the standard deviation along x-axis; YStdDist represents the standard deviation along y-axis; y/x-axis represents the flattening degree of ellipsoid.

Table 6 Regression results of the panal Tobit model for CLUE in China from 2000 to 2020

Variable	Regression coefficient		
	Whole country	MPAs	Non-MPAs
MCI	$0.0980\pm0.0442^{**}$	0.0306 ± 0.0554	$0.1130\pm0.0587^{*}$
GPC	$0.0788\pm0.0074^{***}$	$0.0671\pm0.0110^{***}$	$0.0765\pm0.0101^{***}$
II	$-0.2240\pm0.0783^{***}$	$-0.3020\pm0.1010^{***}$	$-0.2180\pm0.1030^{**}$
STI	$2.0760\pm0.8870^{**}$	$3.8660\pm1.2210^{***}$	1.1420 ± 1.2700
SAL	$0.0931\pm0.0202^{***}$	$0.0944\pm0.0256^{***}$	$0.1100\pm0.0263^{***}$
Constant	$0.1870\pm0.0549^{***}$	$0.3020\pm0.0673^{***}$	$0.1740\pm0.0692^{**}$
Wald χ^2 test	341.69^{***}	158.98^{***}	155.41^{***}
Likelihood ratio test	302.29^{***}	154.48^{***}	137.96^{***}
n	651	273	378

Note: n is the number observations. MPAs, major grain-producing areas; non-MPAs, non-major grain-producing areas; *, $P<0.10$ level; **, $P<0.05$ level; ***, $P<0.01$ level. Mean±SD.

4 Discussion

As depicted in Figures 2 and 3, both in China as a whole and in most provinces, autonomous regions, and municipalities, CLUE exhibited a pattern of initial decrease and subsequent increase throughout the research period, which aligns with the conclusions of Xie et al. (2018). This showed that cultivated land in China is being used more sustainably. It should be noted that from 2013 to 2014 (Fig. 2), CLUE basically remained unchanged, which may be related to the introduction and revision of relevant laws, such as the "Environmental Protection Law", "Water Pollution Control Law", and "Soil and Water Conservation Law". Regarding spatial variations, CLUE in China exhibited spatial agglomeration (Fig. 4), which corroborates the findings of Chai et al. (2023).

However, interestingly, the CLUE in MPAs was lower than that in non-MPAs. It is important to acknowledge that China's food security heavily relies on MPAs, but the utilization of cultivated land is not as efficient as initially presumed. This may indicate that the cultivated land use pattern in MPAs is at the expense of sustainability. Moreover, the barycentre predominantly resided in the central region of China, specifically in Henan Province (Fig. 5; Table 4). The trajectory of barycentre movement presented a "P" shape, with the capital city of Henan Province, Luoyang City, serving as the focal point. This observation result could be attributed to the geographical location of Henan Province. Therefore, it is feasible to construct cultivated land protection projects with Henan Province as the centre (Wang and Zhang, 2013).

Based on the regression results in Table 6, it is necessary to conduct further analysis to clearly show why each factor has an impact on CLUE. As a characterization index of natural condition dimension, the MCI is a basic factor that affects CLUE. The MCI in MPAs did not exhibit a significant impact on CLUE. In contrast, the MCI in non-MPAs can significantly improve CLUE. This can be attributed to the unsustainability of cultivated land caused by long-term and intensive land use, which is undertaken to ensure national food security, as noted by Niu and Fang (2019). In other words, the farmers invested in many production factors, used high-tech means, and implemented fine management to maximize the output of agricultural products, which relaxes the constraints of natural condition on cultivated land use to some extent. Additionally, the complex and multidimensional nature of economic and social development within MPAs may also contribute to the lack of significance in the relationship between MCI and CLUE in MPAs (Zhang et al., 2017a). From a regional economic development level perspective, provinces, autonomous regions, and municipalities with high GPC had greater advantages in agricultural inputs such as capital, policy, and technology and science, which are key points to improving CLUE. Moreover, in China, increased agricultural labour has transferred to secondary and tertiary industries in past decades (Benjamin, 1992; Wang et al., 2007), which also contributes to the concentration of cultivated land. The GPC had almost the same impact on CLUE in the whole country, regardless of whether it is MPA, which shows that the effect of economic level on the sustainable use of cultivated land is universal. Therefore, the important role of economic development cannot be ignored during the process of farmland utilization and protection. The II had the greatest negative impact on CLUE in China during 2000–2020, which contradicts the notion that II is advantageous for agricultural production (Huang et al., 2006). Compared to its counterparts, II in MPAs reduced CLUE to a greater extent. A possible explanation for this difference might be that an expansion in the irrigated area leads to more consumption of fossil fuels and agricultural inputs, thereby contributing to higher carbon emissions and nonpoint source pollution, then ultimately, lower CLUE in MPAs. The STI was undoubtedly the most important factor affecting CLUE, particularly in MPAs. The greater the investment in science and technology, the greater the innovation in that field. As a result, new agricultural equipment and information service platforms should be used to monitor farmland utilization in real time and optimize unreasonable production models. Furthermore, farmers can benefit from increased technical guidance and explore the untapped potential of cultivated land, enabling its scientific and rational utilization. However, non-MPAs are not the main contributors to agricultural production in China, so they do not rely on technological means to pursue ultrahigh yields. The SAL served as an indicator of the scale of operation in agriculture. Expanding the management scale can effectively reduce the use of chemical fertilizers and pesticides (Gao et al., 2021), facilitating the allocation of production factors and ultimately enhancing CLUE (Duan et al., 2021). However, especially in a country as large as China with weak agriculture, it is difficult to achieve large-scale agricultural service and operation due to the fragmentation of cultivated land, thus hindering the sustainable use of farmland. Therefore, the expansion of SAL increased CLUE regardless of whether it is MPA.

This paper provides several policy implications based on the findings. First and foremost, it is imperative to give greater attention to the mitigation of carbon emissions and the control of nonpoint source pollution during the utilization of cultivated land. Relevant departments should

start from the sources of pollution and adopt a greener and more low-carbon model to use cultivated land. Also, it is essential to regulate the excessive utilization of production inputs (such as pesticide and chemical fertilizer). Promoting the adoption of low-carbon fertilizers and reducing the quantity of highly pollution pesticides are crucial steps in this regard. Second, enhancing support for agricultural scientific and technological innovation within MPAs can significantly contribute to the improvement of CLUE. The government needs to invest more research and development funds in this field. Moreover, government should cooperate with universities and research institutions to improve innovation capacity and popularize agricultural technology. Third, relevant governments should strive for a balance between economic development and ecological conservation and formulate proposals for the utilization of cultivated land. Strict measures should be implemented to prohibit illegal encroachment on cultivated land during the processes of urbanization and industrialization. After all, human activities are more destructive than climate change (Djihouessi et al., 2022).

Several limitations need to be noted. First, cultivated land not only produces carbon emissions but can also causes carbon sinks (Tang et al., 2020). However, we only considered carbon emissions when calculating CLUE in the study, which may underestimate CLUE and reduce the accuracy of measurements. Future research in this field should incorporate carbon sinks into the evaluation system. Second, despite illustrating the spatial-temporal evolution of CLUE and its influencing factors, the direct impact of CLUE on agricultural production remains uncertain. The relationship between the two should be explored in future research.

5 Conclusions

This study used the GB-US-SBM model to measure the CLUE of 31 provinces, autonomous regions, and municipalities in China from 2000 to 2020. Based on the measurement data, we adopted the boxplot, barycentre model, and SDE model to analyze the spatial-temporal evolution of CLUE. Finally, the panel Tobit model was used to explore the influencing factors of CLUE. The main conclusions are as follows: first, China's CLUE generally showed an upward trend, with the highest growth rate occurring during 2015–2020. Except for Hainan and Sichuan provinces and Xizang Autonomous Region, CLUE in other provinces, autonomous regions, and municipalities increased at different rates. Second, there was an obvious spatial agglomeration effect in CLUE, showing a northeast–southwest strip distribution. In addition, the movement path of barycentre revealed a "P" shape, with Luoyang City, Henan Province, as the centre. Third, STI played the most vital role in improving CLUE, whereas II had a negative impact. And the impact effects of the five influencing factors on MPAs and non-MPAs existed obvious differences.

In a country such as China where the economy and society are experiencing rapid transformation, any development model that sacrifices CLUE should be abandoned. Unfortunately, China still has a long way to go in achieving sustainable land use. Furthermore, when incorporating land resources into an overall development plan, the differences among different provinces, autonomous regions, and municipalities, especially between MPAs and non-MPAs, should be taken into consideration. This approach may be a feasible way to alleviate the contradiction between people and land in China.

Conflict of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

This work was supported by the National Natural Science Foundation of China (72373117), the Chinese Universities Scientific Fund (Z1010422003), the Major Project of the Key Research Base of Humanities and Social Sciences of the Ministry of Education (22JJD790052), and the Qinchuangyuan Project of Shaanxi Province (QCYRCXM-2022-145).

Author contributions

Conceptualization: LI Shaoting, REN Yanjun; Data curation: MU Na, LI Shaoting; Methodology: Li Shaoting, MU Na; Formal analysis: LI Shaoting; Writing - original draft preparation: LI Shaoting, MU Na; Writing - review and editing: REN Yanjun, Thomas GLAUBEN; Funding acquisition: REN Yanjun; Visualization: LI Shaoting. All authors approved the manuscript.

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